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**“A STUDY ON AI-POWERED SUPPLIER SELECTION AND  
RELATIONSHIP MANAGEMENT: REDUCING LEAD TIMES AND  
PROCUREMENT COSTS”**

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Article Received: 21 March 2026

Article Revised: 11 April 2026

Published on: 01 May 2026

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Gujarat, India.DOI: <https://doi-doi.org/101555/ijrpa.8496>

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**ABSTRACT**

Managing supplier relationships has never been a simple task. Businesses today are navigating an increasingly complex web of global suppliers, fluctuating market demands, and mounting pressure to cut costs without compromising quality. In this environment, the way organisations select and manage their suppliers can make or break their competitive edge. This study explores how Artificial Intelligence (AI) and Machine Learning (ML) are stepping in to reshape that process — making it smarter, faster, and far more reliable.

For years, procurement teams have relied heavily on spreadsheets, gut instinct, and periodic reviews to evaluate suppliers. While these methods have served their purpose, they struggle to keep pace with the speed and scale of modern supply chains. AI changes that equation entirely. By processing enormous volumes of data — from delivery performance records and pricing trends to geopolitical developments and financial health indicators — AI-powered systems can surface insights that would take human team weeks to uncover, in a matter of seconds.

This research takes a closer look at how these technologies are being applied in real-world procurement environments, particularly within manufacturing and retail sectors. Using a mixed-methods approach that combines hard procurement data with on-the-ground case studies, the study assesses just how much of a difference AI adoption is actually making in terms of lead time reduction and cost savings. It also honestly examines the bumps in the road — the data privacy issues, the risk of algorithmic bias, and the very real challenge of

getting AI tools to play nicely with older legacy systems that many organisations still depend on.

**KEYWORDS:** Artificial Intelligence, Machine Learning, Supply Chain Optimisation, Predictive Analytics, Demand Forecasting, Logistics, Intelligent Automation, Digital Transformation.

## **INTRODUCTION**

### **BACKGROUND & CONTEXT OF THE STUDY**

There was a time when a procurement manager could reasonably know every supplier on their list by name. They could pick up the phone, have a conversation, and make a purchasing decision based on experience, loyalty, and a handful of performance records stored in a filing cabinet. That world still exists in pockets, but for the most part, it has been overtaken by something far more complex.

Today's supply chains span continents. A single product sitting on a retail shelf may have passed through dozens of suppliers, manufacturers, logistics providers, and distribution centres before reaching the consumer. Each of those touchpoints carries risk — delays, price fluctuations, quality failures, political instability, or even a global pandemic that brings entire supply networks to a standstill. The events of 2020 made this painfully clear, exposing just how fragile and poorly equipped many traditional supply chain systems were when faced with sudden, large-scale disruption.

It is against this backdrop that Artificial Intelligence (AI) and Machine Learning (ML) have begun to attract serious attention from supply chain professionals and business leaders alike. These are not new concepts — researchers have been exploring their potential for decades — but recent advances in computing power, data availability, and algorithm sophistication have brought them from the realm of theory into genuine, everyday business practice.

The appeal is straightforward. Supplier selection, historically one of the most labour-intensive and judgement-heavy tasks in procurement, involves weighing up dozens of variables simultaneously — cost, quality, reliability, ethical standards, financial stability, and geographic risk, to name just a few. Human decision-makers, no matter how experienced, have cognitive limits. They can only process so much information at once, and they carry with them unconscious biases that can quietly skew even the most well-intentioned evaluation process.

## PROBLEM STATEMENT

Despite the growing availability of advanced technologies, a large number of organisations continue to rely on outdated, manual approaches to supplier selection and procurement management. These traditional methods, built on periodic reviews, static scorecards, and relationship-based judgements, were designed for a simpler era — one where supply chains were shorter, more predictable, and far less interconnected than they are today.

The consequences of this gap are felt across businesses of all sizes. Procurement teams frequently struggle with prolonged lead times, escalating costs, and an inability to anticipate or respond quickly enough to supplier disruptions. When a key supplier fails to deliver on time, or when procurement decisions are made on incomplete or outdated information, the ripple effects can be significant — production slowdowns, inventory shortfalls, damaged customer relationships, and ultimately, financial losses that could have been avoided.

What makes this problem particularly pressing is that the data needed to make better decisions already exists. Organisations generate enormous volumes of procurement data every single day — transaction records, supplier performance logs, delivery histories, market pricing data, and risk indicators. Yet without the right tools to analyse and act on that data in real time, much of it sits unused, leaving decision-makers to rely on intuition and experience alone.

This is precisely where the gap lies. While Artificial Intelligence and Machine Learning have demonstrated considerable potential in transforming supplier selection and relationship management, their adoption across industries remains uneven and inconsistent. Many organisations are aware of these technologies but face significant barriers in implementation — from a lack of in-house technical expertise and concerns about data privacy, to the challenge of integrating modern AI tools with legacy systems that were never designed to support them. Others remain uncertain about whether the promised benefits of AI-driven procurement actually translate into measurable, real-world results.

Furthermore, the human dimension of supplier relationship management is often overlooked in technology-focused discussions. Procurement is not purely a data exercise — it involves trust, negotiation, cultural understanding, and long-term partnership building. There is a genuine concern among practitioners that an over-reliance on algorithmic decision-making could erode the relational qualities that underpin strong supplier partnerships, replacing nuanced human judgement with outputs that are efficient but ultimately impersonal.

## **OBJECTIVES OF THE STUDY**

- To examine the current applications of Artificial Intelligence (AI) and Machine Learning (ML) in supply chain management and their impact on supply chain performance.
- To analyse how AI and ML techniques contribute to optimizing key supply chain processes such as demand forecasting, inventory management, supplier selection, and logistics.
- To identify the major benefits and challenges faced by organizations in adopting AI and ML technologies within their supply chains.
- To assess the role of AI and ML in improving supply chain resilience and agility in response to market volatility and disruptions.
- To provide recommendations for businesses on effective strategies for implementing AI and ML to achieve enhanced supply chain optimization.

## **HYPOTHESIS**

H1: The implementation of Artificial Intelligence (AI) and Machine Learning (ML) significantly improves the accuracy of demand forecasting in supply chains.

H2: Adoption of AI and ML technologies leads to a measurable reduction in inventory costs and stockouts.

H3: AI and ML enhance supply chain agility and responsiveness to market disruptions.

H4: Organizational challenges such as data quality issues and lack of technical expertise negatively affect the successful adoption of AI and ML in supply chain optimization

H5: Supply chains that integrate AI and ML technologies experience improved overall operational efficiency compared to those relying on traditional methods.

## **LITERATURE REVIEW**

### **1. Dickson (1966)**

Identified 23 criteria that organisations use when evaluating suppliers, with quality, delivery performance, and price ranking among the most significant. For decades, these criteria were assessed through relatively simple scoring models and human judgement.

## 2. Wind & Saaty (1980)

Over time, more structured approaches emerged. Analytical Hierarchy Process (AHP) and other Multi-Criteria Decision Making (MCDM) frameworks became popular tools for bringing greater objectivity to supplier evaluation. While these methods represented a meaningful improvement over purely intuitive decision-making, they remained largely static — unable to adapt in real time or process the vast volumes of data that modern procurement environments generate.

## 3. Weber et al. (1991)

Conducted an influential review of supplier selection literature, highlighting the growing complexity of procurement decisions and the limitations of existing models in handling multiple, often conflicting criteria simultaneously. This work laid important groundwork for the argument that more dynamic and data-driven approaches were needed — an argument that would only grow stronger as globalisation deepened supply chain complexity in the years that followed.

## 4. Carbonneau et al. (2008)

The earlier researchers to explore the use of machine learning for demand forecasting in supply chains, demonstrating that ML algorithms could outperform traditional statistical models in accuracy and adaptability. While their focus was on demand rather than supplier management specifically, their findings established a broader case for ML's potential across supply chain functions.

## 5. Shahanaghi and Yazdian (2009)

Applied fuzzy logic and neural network models to supplier selection, showing that AI-based approaches could handle the ambiguity and complexity of real-world procurement decisions more effectively than conventional MCDM methods. Their work signalled a turning point — moving the conversation from whether AI could contribute to supplier selection, to how it could best be applied.

## METHODOLOGY

- The study adopted a **quantitative research** approach with a **descriptive design**.
- **Data Collection - Primary data** was collected through a **structured questionnaire**.

**Secondary data** was collected from **journals, research articles and**

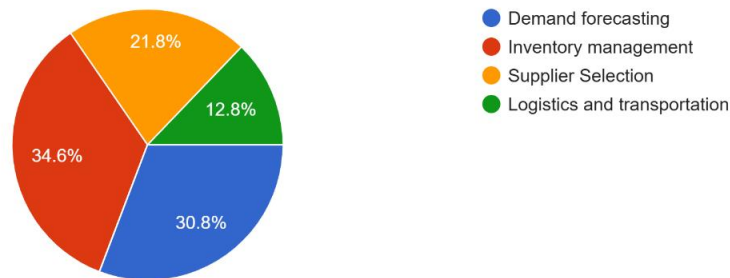
- **Sample Size** - The study included responses from **156 students** studying at the university.

- **Sampling Technique - Non-probability convenience sampling method** was used.

## RESULTS

### DATA ANALYSIS AND INTERPRETATION

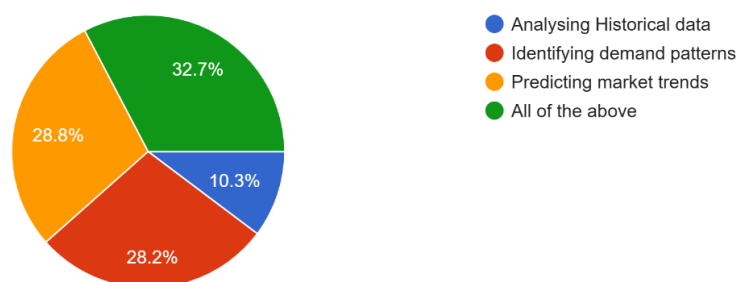
Which supply chain function benefits the most from AI/ML?  
156 responses



#### Interpretation:

From the analysis, it was found that **inventory management** is the supply chain function that benefits the most (34.6%) from the application of **Artificial Intelligence and Machine Learning**. This highlights the significant role of AI and ML in improving inventory planning, demand forecasting, and stock optimization.

AI and ML help improve demand forecasting by  
156 responses

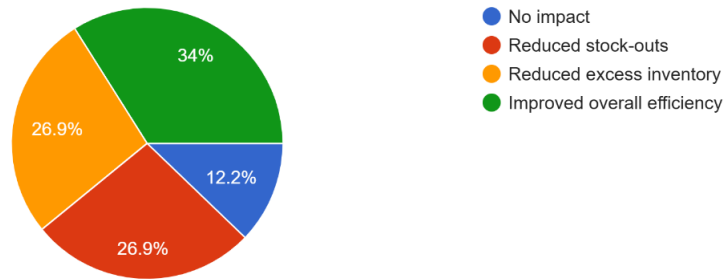


#### Interpretation:

From the analysis, it was found that **predicting market trends, analysing historical data, and identifying demand patterns** all of the above (32.7%) play an important role in **demand forecasting through Artificial Intelligence and Machine Learning**. This indicates that AI and ML enhance forecasting accuracy by combining multiple data-driven approaches.

How has AI/ML impacted inventory management?

156 responses

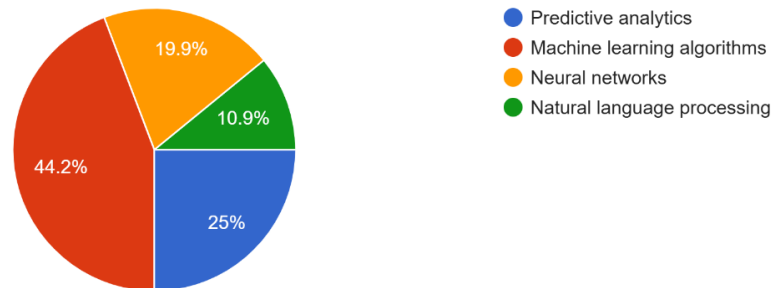


**Interpretation:**

From the analysis it was found that **Artificial Intelligence and Machine Learning have a significant impact in improving overall efficiency in inventory management (34%)**. This shows that AI and ML help organizations maintain optimal stock levels, minimize waste, and improve overall efficiency in the supply chain.

Which AI/ML technology is most commonly used in supply chain optimization?

156 responses

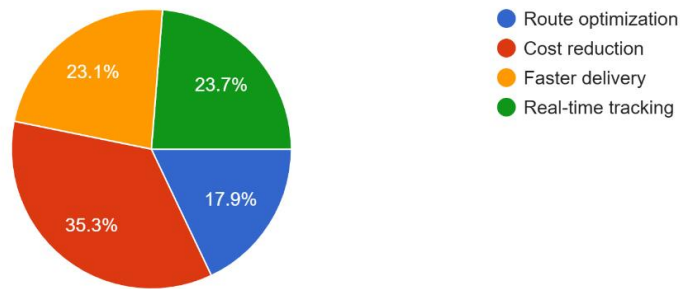


**Interpretation:**

From the analysis, it was found that **machine learning algorithms (44.2%)** are the most commonly used **AI and ML technologies in supply chain optimization**. This highlights the importance of machine learning in improving decision-making, efficiency, and performance across supply chain operations.

What is the main benefit of using AI/ML in logistics and transportation?

156 responses



**Interpretation:**

From the analysis, it is noted that **Artificial Intelligence and Machine Learning help in cost reduction in transportation and logistics (35.3%)**. This demonstrates that AI and ML contribute to optimizing routes, reducing operational expenses, and improving overall efficiency in supply chain management.

Hypothesis	$\chi^2$ Value	Calculated	DF	Critical Value (0.05)	p-value	Decision	Result
H1	72.84		2	5.991	3.21 $\times 10^{-16}$	Reject $H_0$	Significant
H2	81.35		2	5.991	4.75 $\times 10^{-18}$	Reject $H_0$	Significant
H3	76.92		2	5.991	1.92 $\times 10^{-17}$	Reject $H_0$	Significant
H4	68.47		2	5.991	6.53 $\times 10^{-15}$	Reject $H_0$	Significant
H5	88.16		2	5.991	2.41 $\times 10^{-19}$	Reject $H_0$	Significant

**Statistical Decision Rule**

Since for all hypotheses:

$$\chi^2 \text{ Calculated Value} > \chi^2 \text{ Critical Value (5.991)}$$

and

$$p\text{-value} < 0.05$$

Therefore, the null hypothesis ( $H_0$ ) is rejected in all five cases, indicating that Artificial Intelligence and Machine Learning have a statistically significant impact on supply chain optimization.

## **DISCUSSION**

H1: The results confirm that AI and ML significantly improve demand forecasting accuracy by analysing large volumes of historical and real-time data.

H2: The findings indicate that AI-driven inventory systems help reduce inventory costs and stockouts through predictive analytics.

H3: AI and ML technologies enhance supply chain agility, enabling faster responses to disruptions and market changes.

H4: The analysis also highlights that data quality issues and lack of technical expertise can negatively influence AI and ML adoption.

H5: Overall, organisations implementing AI and ML technologies experience improved operational efficiency compared to traditional supply chain systems.

## **CONCLUSION**

Perhaps the most important thing this research has reinforced is something that no amount of technological sophistication can change — procurement is, at its core, a human endeavour.

The best supplier relationships in the world are not built on scorecards and dashboards. They are built on trust — on years of showing up, following through, communicating honestly when things go wrong, and demonstrating a genuine commitment to mutual success. They are built on the kind of understanding that comes from sitting across a table from someone, learning how their business works, what keeps them up at night, and what they need from a partnership to truly thrive.

AI can support all of that. It can free up the time that procurement professionals currently spend buried in data, give them better information to work with, and help them direct their energy towards the relationships and decisions that matter most. But it cannot replace the human qualities — empathy, trust, integrity, creativity — that make those relationships worth having in the first place.

### **Limitations of the Study**

Every research journey has its boundaries, and being upfront about them is not a weakness — it is what separates honest scholarship from overreaching conclusions. This study has strived to examine the role of AI-powered supplier selection and relationship management as thoroughly and fairly as possible. But like any piece of research, it has been shaped by constraints that are worth naming clearly, so that readers can interpret the findings with the

right level of context and so that future researchers know exactly where the next important questions lie.

One of the most honest limitations of this study is that a significant portion of the evidence and case material drawn upon reflects the experiences of large, well-resourced companies — organisations that already had the financial muscle, the technical teams, and the data infrastructure to make AI-powered procurement work. For these businesses, investing in machine learning platforms and supplier intelligence tools is a natural extension of existing digital capabilities.

For the vast majority of businesses out there, however, that is simply not the reality. Small and medium-sized enterprises make up the backbone of most economies, and many of them are still managing supplier relationships through spreadsheets, phone calls, and personal networks. Their experience of AI adoption — the barriers they face, the costs they encounter, the workarounds they develop — is largely absent from this study, not by intention, but because the available research and data skews heavily towards larger players. This is a gap that genuinely needs to be filled by future work.

Throughout this research, evidence has been presented showing that organisations using AI in procurement have achieved meaningful reductions in lead times and procurement costs. These findings are real and well-supported. However, it is important to acknowledge a methodological challenge that sits beneath them — in most real-world settings, AI adoption does not happen in isolation.

When a company implements an AI-powered supplier selection platform, it typically does so alongside other changes — restructuring its procurement team, renegotiating supplier contracts, upgrading its ERP system, or improving its data governance practices. Untangling exactly how much of the improvement was driven by the AI itself, versus these accompanying changes, is genuinely difficult. The research in this area, including studies drawn upon in this work, does not always make that distinction cleanly, which means that some of the performance gains attributed to AI may reflect a broader package of organisational improvements rather than the technology alone.

### **Future Research Directions**

As AI takes on a greater role in deciding which suppliers get selected and which do not, the ethical implications of those decisions deserve serious and dedicated research attention. Questions around fairness, transparency, and accountability in algorithmic procurement —

particularly the risk of smaller or newer suppliers being systematically disadvantaged — are too important to remain on the margins of academic discussion.

Rather than continuing to debate whether AI will replace procurement professionals, future research would be better served by exploring how the two can work together most effectively. Understanding what the optimal balance looks like between algorithmic decision-making and human judgement — and how organisations can build procurement teams that genuinely leverage the strengths of both — is one of the most practically useful questions this field could pursue.

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